

*Citation for published version:*

Li, R, Wang, Z, Le Blond, S & Li, F 2014, Development of time-of-use price by clustering techniques. in *PES General Meeting/Conference & Exposition, 2014 IEEE* ., 6939335, IEEE, PES General Meeting/ Conference & Exposition, 2014 IEEE , National Harbor, USA United States, 27/07/14.  
<https://doi.org/10.1109/PESGM.2014.6939335>

*DOI:*

[10.1109/PESGM.2014.6939335](https://doi.org/10.1109/PESGM.2014.6939335)

*Publication date:*

2014

*Document Version*

Early version, also known as pre-print

[Link to publication](#)

## University of Bath

### Alternative formats

If you require this document in an alternative format, please contact:  
[openaccess@bath.ac.uk](mailto:openaccess@bath.ac.uk)

#### General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

#### Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

# Development of Time-of-Use Price by Clustering Techniques

Ran Li, Zhimin Wang, Simon Le Blond and Furong Li

Department of Electronic and Electrical Engineering

University of Bath,

Bath, UK

rl272@bath.ac.uk

**Abstract**— Active demand side response (DSR) from domestic customers can generate benefits in terms of reducing energy costs for customers and shaving peak demand for distribution network operators (DNOs). However, real-time price (RTP) is considered to be too dynamic for customers to response. Also, it is infeasible for most energy storage equipment to response to variable signals, such as RTP, as they can only charge/discharge a few cycles throughout a day. Due to these constraints, time-of-use (TOU) price is a more natural price signal for DMS. This paper proposes a novel statistical method to successfully convert RTP to TOU that captures the most significant price variations without comprising too much accuracy in total energy revenue from customers. The proposed method adopts hierarchical clustering techniques to group RTP into clusters, and each settlement period is assigned to one of the clusters to form a TOU pattern. For each cluster of the TOU tariff pattern, the tariff rate is determined by keeping the total customer revenue unchanged.

**Index Terms**—clustering, demand response, energy cost, real-time price, time-of-use tariff

## I. INTRODUCTION

Wholesale energy cost, which consists of fuel procurement, operating costs and capital costs of energy generation, is the greatest element of household electricity bill. It covers over half of the of the end-users' bill according to the survey by the Office of Gas and Electricity Markets (Ofgem) in the UK [1]. Since wholesale energy costs are still likely to be maintained as a significant part of the customers' end-bill in the future [2], effective responses to energy price variation could lead to significant energy cost saving to end consumers.

Energy price varies every half hour in Great Britain's wholesale electricity market. If the change of energy price in a settlement day is expected to be shown to demand side, real-time pricing (RTP) is the most appropriate pricing scheme to reflect wholesale energy price variation. However, for mass consumers in domestic sector, real-time variable tariffs could scarcely guide the demand side response (DSR) effectively since its frequent variation of price rate is generally considered

too complex for small electricity users. In order to determine appropriate time windows or time intervals for efficient DSR, the dynamics in half-hourly varied energy prices should be reflected and translated into time-of-use (TOU) tariff with less price variation and specific time intervals for defined tariff rates. Settlement periods of a day are then separated into several intervals with different types of rate, e.g. peak and off-peak hours and rates [3].

The challenge of the TOU tariff determination lies on i) how to set the most reasonable time interval for different price rates; ii) how to reflect real-time varied wholesale price appropriately. A number of previous studies have been conducted on TOU pricing investigation [2, 4]. They present the characteristics of TOU tariffs and compare them with RTP tariffs to indicate the uncertainty and volatility of prices in RTP. Besides, many pricing approaches develop mathematical models to estimate time-of-use (TOU) prices for a retail electricity market [5-8]. However, the numbers of tariff types and time intervals for pricing are predefined and they do not explain the reasons for the proposed rates settings in TOU pricing.

This paper develops a novel approach to determine TOU tariff for DSR from domestic sector. It aims to successfully convert wholesale RTP to TOU without compromising too much precision. This pricing scheme is significantly different from other pricing approaches as it employs hierarchical clustering approach to determine pricing blocks without pre-knowledge. The advantage of the proposed TOU pricing scheme can be seen from the following two aspects: i) each half-hour settlement period in RTP can be clustered in to the group in which all the elements have the least price rate difference; ii) the selected tariff rate number, i.e. the number of clusters in clustering, is optimized considering both accuracy and feasibility of implementation.

The investigation of the proposed TOU pricing scheme is carried out for four seasons and two day types in a settlement year. The detailed investigation process can be summarised as: i) wholesale electricity prices for a whole year are represented by typical price for each season and day type; ii) typical

---

The work is sponsored by Western Power Distribution

wholesale prices are converted to RTP for domestic customers; iii) cluster 48 time intervals into appropriate clusters based on RTP; iv) for each cluster of TOU, the tariff rate is determined by maintaining the total bill unchanged, i.e. for a given load, the bill would be same charged either by RTP or TOU.

The reminder of the paper is organised as follows: Section II introduces the overall methodology of the transformation of TOU from RTP. Section III demonstrates the implementation of developing TOU with proposed method. Section IV demonstrates the designed TOUs. Conclusions are drawn in Section V.

## II. PROPOSED METHODOLOGY

RTP can be translated into TOU with several pre-defined periods and tariff types, e.g. peak, shoulder, and off-peak tariff. Time of day is then separated into several intervals, each belonging to one of the defined tariff types. The overall proposed method to develop TOU price signal from RTP signal can be achieved through three general steps:

- i) Number of tariff types: investigate the number of tariff types required to represent the variation of RTP.
- ii) Width of each interval: based on the defined tariff types, each settlement period is assigned to one of the tariff types. It is essential to determine the number of divided intervals per day and the duration of each interval.
- iii) Height of interval: to determine the accurate tariff rate of each tariff type.

The flowchart illustrating breakdown steps of the development of TOU is shown in figure 1. Following the same practice of wholesale RTP, TOU is designed for different season and day types at half-hourly basis.

The number of tariff types required and the assignment of settlement periods largely depend on the RTP. For example, a steady RTP can be well represented by flat rate while a very dynamic RTP would require many different tariff types and time intervals. As the patterns and rates of RTP vary significantly through the year and countries, it would be inaccurate to set a deterministic envelope for each tariff type. In order to find the natural group of the RTP without pre-knowledge, hierarchical clustering is adopted to calculate the distances between the prices of settlement periods, which indicate the similarity between periods. The initial set-up sees each period being classified as its own cluster and clusters then merged, according to similarity measure, until ultimately there is again a single cluster. Based on this hierarchical clustering, the TOU procedure can be implemented by following steps:

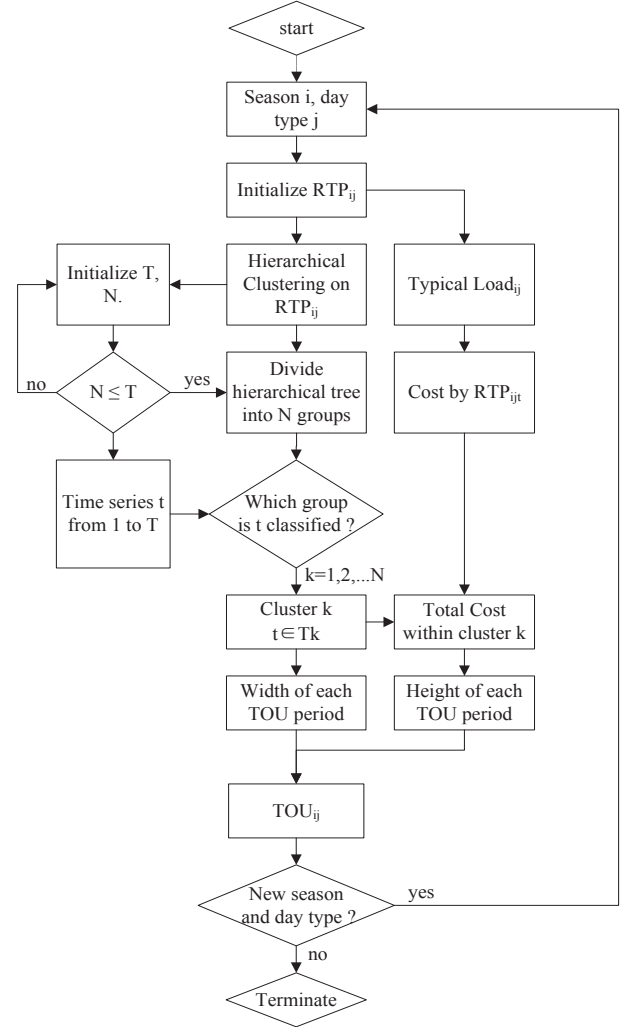


Figure 1 Flowchart of the development of TOU

- i) For different number of tariff types, i.e. clusters, the within-group dissimilarity is calculated. The dissimilarities are expected to decrease with the increase of clusters. After certain number  $N$  of clusters, the decrease rate will drop significantly, which indicates much less effects with further partition. The number of clusters can be tested from 1 to the number of total individual settlement periods  $T$ .
- ii) Each settlement period is classified into one of the  $N$  clusters (tariff types) so that the RTP of a day is divided into several time intervals.
- iii) The rate of each tariff of TOU is determined by ensuring a same energy cost. For a given load, the total electricity bill should be the same charged either RTP or TOU. The typical domestic load profile [9] of each season and day type is adopted here to calculate total energy cost.

### III. DEVELOPMENT OF TOU

#### A. Real Time Price

The RTP in this paper is developed through capturing whole sale energy price variations from 2012 to 2013 up to October [10]. As RTP only reflects a part of supply chain cost, the other components are subsequently added to reflect the cost of delivery [11].

#### B. Number of tariff types and time interval determination by clustering

For any season and day type, the half-hourly daily RTP can be denoted as a  $1 \times 48$  vector  $(x_1, x_2, \dots, x_{48})$ . Hierarchical clustering is adopted in this study to partition the RTPs of each settlement period into clusters. The calculation of the distances  $d_{k,j}$  between two prices  $x_k$  and  $x_j$  is determined by (1)

$$d_{k,j} = \|x_k - x_j\| = \sqrt{(x_k - x_j)^2} \quad (1)$$

Where  $x_k$  and  $x_j$  are the real time prices at  $k^{\text{th}}$  and  $j^{\text{th}}$  settlement period.

Next step is grouping of the settlement periods into hierarchical cluster tree by merging together those with the smallest distances on their prices. The merged settlement periods then form a cluster. After the merging process, a new distance is calculated between existing clusters and form new clusters [12]. The process of forming new clusters is repeated until only one-cluster remains. The distances between clusters are calculated by the Ward distance in (2), assuming A and B are two clusters during the process.

$$d_{A,B} = \frac{1}{|A||B|} \sum_{x_a \in A} \sum_{x_b \in B} \sqrt{(x_a - x_b)^2} \quad (2)$$

Where  $x_a$  and  $x_b$  are prices of settlement periods which were clustered into cluster A and B in the previous step.

For each number of clusters, the average within-group distance [13] is calculated. The lower average within-group distance indicates a higher similarity within group. The change along number of clusters are listed in Table I with winter weekday and summer weekend as examples.

When prices of all settlement periods are grouped in 1 cluster, the within-group distance are very high at 47 for both scenarios. It starts to decrease when similar prices are grouped in clusters. For winter weekday, it decreases quickly to 4.61 at 3 clusters, and further partition only gives slight improvements. For summer weekend, the decrease is relatively steady. The decrease from 3 clusters to 4 clusters is close to that from 2 to 3. Further after 4 clusters, the decrease becomes much slower. Therefore in the design of TOU, 3 tariff types would be sufficiently representative for winter weekday while 4 tariff types are likely to be required for summer weekend.

TABLE I AVERAGE WITHIN-GROUP DISTANCE ALONG DIFFERENT NUMBER OF CLUSTERS

Cluster \ Scenario	Winter Weekday (£/MWh)	Summer Weekend (£/MWh)
1	47	47
2	12.64	13.99
3	4.61	8.26
4	2.93	2.98
5	2.21	1.69
6	0.94	1.40

Taking the winter weekday as an example, each settlement period can be therefore assigned into one of the three clusters, i.e. peak, shoulder and off-peak. As shown in dendrogram of figure 2, the 48 settlement periods of RTP are grouped based on their price distances, which are reflected on the height of y-axis. Three clusters will be partitioned as shown in the red boxes in the figure.

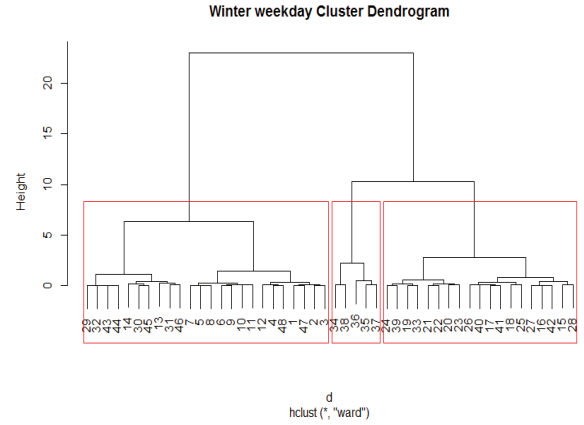


Figure 2 Hierarchical clustering for real time prices intervals

#### C. Determination of TOU rates

The clustering process has determined the number of tariff and corresponding time intervals, as listed in Table II. It can set the overall shape of the TOU following the trend of RTP.

However, the derived TOU contains only shape information, i.e. the length of each period, but no information about the exact price rate, i.e. the height of each period. For the rate of each tariff type, it is most convenient to use average RTP within periods of each cluster. However, this way is unable to express the cost variance because the load is not flat during time periods. The average price within cluster, which takes each settlement period by the same weight, would compromise the TOU's representativeness of RTP in terms of cost variances.

TABLE II CLUSTERING OF THE SETTLEMENT PERIODS OF REAL-TIME PRICE OF WINTER WEEKDAY

Time	Tariff Type
00:00 -- 07:00	Tariff One
07:01 -- 14:00	Tariff Two
14:01 -- 16:30	Tariff One
16:31 -- 19:00	Tariff Three
19:01 -- 21:00	Tariff Two
21:01 -- 23:59	Tariff One

The rate for each cluster in this paper is determined by (3). The idea is that for a typical load, the total energy cost of settlement periods within a cluster should be the same, charged by either TOU or RTP tariff.

$$TOU_{ij,k} = \frac{\sum_{t \in k} RPT_{ij,t} * L_{ij,t}}{\sum_{t \in k} L_{ij,t}} \quad (3)$$

Where  $TOU_{ij,k}$  is the tariff rate of TOU of season  $i$ , day type  $j$  and tariff type (cluster)  $k$ ;  $L_{ij,t}$  is the typical domestic customer load;  $t$  is the set of settlement periods within cluster  $k$ ; and  $RPT_{ij,t}$  is the real-time price.

#### IV. RESULTS

The TOUs are developed for the whole year's RTP by 4 seasons and 2 day types. The results of total 8 scenarios all overall conform well to the RTP. Figure 3 shows the winter weekday as an example. It is designed with 3 tariff rates and 6 time intervals per day. TOU under most scenarios can be well expressed by 3 tariff types while the autumn weekday and the summer weekend require 4 tariff types to reflect the variations of RTP. All developed TOUs have no more than 7 time intervals per day, which can mitigate some of the burden on battery and make customer response easier.

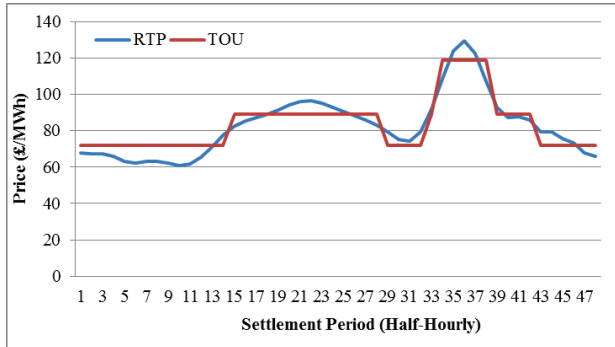


Figure 3 RTP and developed TOU for winter weekday

Figure 4 and figure 5 demonstrate the occasion for summer weekend. If only 3 rate types are adopted here, as shown in figure 4, the daytime peak cannot be well reflected as it is substantially higher than evening peak. In order to reflect the differences between daytime and evening peak at the summer weekend, four-rate TOU is developed in figure 5. It clearly shows the trend of RTP and more accurately depicts the rate

difference. The comparison here in turn proves the proposed method in III, where the summer weekend scenario saw an obvious decrease in cluster distance from 3 clusters to 4 clusters.

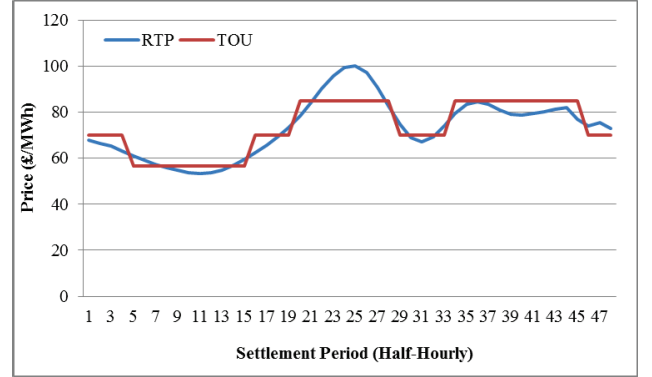


Figure 4 RTP and developed 3-rate TOU for summer weekend

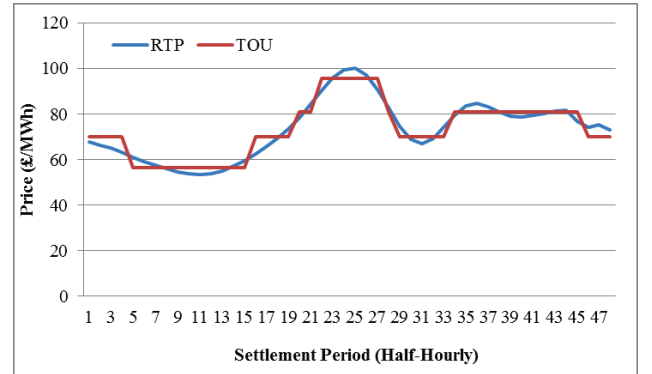


Figure 5 RTP and developed 4-rate TOU for summer weekend

#### V. CONCLUSION

This paper proposes a new method to develop TOU from RTP using clustering techniques, which is able to find the natural group of settlement periods with similar prices. The aim is to transfer the variable price signal into a step price signal to which energy management system can respond. The proposed method presents the first attempt to determine optimum tariff types and time intervals for TOU with high statistical confidence. RTP under most scenarios can be represented by TOU within 3 tariff types and 7 time intervals per day. The demonstration proves that developed TOU not only reflects the largest variation of RTP, but also maintains the energy cost with typical load patterns.

#### REFERENCES

- [1] Ofgem, "Updated household energy bills explained," ed, 2013.
- [2] A. Prandini, "Good, BETTA, best? The role of industry structure in electricity reform in Scotland," *Energy policy*, vol. 35, pp. 1628-1642, 2007.
- [3] Y. Na and Y. Ji-Lai, "Optimal TOU Decision Considering Demand Response Model," in *Power System Technology, 2006. PowerCon 2006. International Conference on*, 2006, pp. 1-5.

- [4] W. Zhimin and L. Furong, "Developing trend of domestic electricity tariffs in Great Britain," in *Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition on*, 2011, pp. 1-5.
- [5] E. Celebi and J. D. Fuller, "A Model for Efficient Consumer Pricing Schemes in Electricity Markets," *Power Systems, IEEE Transactions on*, vol. 22, pp. 60-67, 2007.
- [6] E. Celebi and J. D. Fuller, "Time-of-Use Pricing in Electricity Markets Under Different Market Structures," *Power Systems, IEEE Transactions on*, vol. 27, pp. 1170-1181, 2012.
- [7] O. ChengQi, X. Charlene, X. Jingxia, and L. Feihong, "Time-of-use Price Decision Model of Natural Gas Based on Simulation and Grey Relationships," in *Information Management, Innovation Management and Industrial Engineering (ICIII), 2010 International Conference on*, 2010, pp. 176-179.
- [8] T. Yudong, S. Hongkun, H. Funian, and Z. Yun, "Investigation on TOU pricing principles," in *Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES*, 2005, pp. 1-9.
- [9] L. Ran, G. Chenghong, Z. Yan, and L. Furong, "Implementation of load profile test for electricity distribution networks," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012, pp. 1-6.
- [10] Elexon. UK Electrical Power System Summary Data [Online]. Available: <http://www.bmreports.com>
- [11] OFGEM. Electricity and Gas Supply Market Indicators [Online]. Available: <https://www.ofgem.gov.uk/gas/retail-market/monitoring-data-and-statistics/electricity-and-gas-supply-market-indicators>
- [12] A. A. Freitas, "Data Mining and Knowledge Discovery with Evolutionary Algorithms," *Springer*, 2002.
- [13] G. Chicco, R. Napoli, and F. Piglione, "Comparisons among clustering techniques for electricity customer classification," *Power Systems, IEEE Transactions on*, vol. 21, pp. 933-940, 2006.